ONLINE APPENDIX:

The Technological Uniqueness Paradox

Appendix A1: Variable Descriptions

Table A01 **Variable Description**

Variables	**Descriptions**	**Data Sources**
Adjusted Coverage	The number of analysts covering the firm divided by the number of analysts covering the industry to which the firm belongs.	IBES
Advertising Intensity	The ratio of the firm's advertising expenditure to total operating expense.	Compustat
Analyst Attention	The number of analysts covering the firm.	IBES
Analyst Coverage Dummy	A dummy variable that is equal to 1 if the firm is covered by an analyst.	IBES
Analyst Coverage Loss	The negative of the number of analysts covering the firm.	IBES
Analyst Effort	The negative of the number of other firms that the analyst is covering	IBES
Assets (log)	Natural log of total assets at beginning of the year.	Compustat
Average HHI	The firm's average industry concentration measure based on weighted-sales across the firm's product market segments.	Compustat Segments
Average Market Share	The firm's average market share based on weighted-sales across the firm's product market segments.	Compustat Segments
Cost of Capital (Claus and Thomas, 2001)	The firm's cost of capital based on Claus and Thomas, 2001.	Claus and Thomas, 2001
Cost of Capital (Easton, 2004)	The firm's cost of capital based on Easton, 2004	Easton, 2004
Cost of Capital (Gebhardt et al, 2001)	The firm's cost of capital based on Gebhardt et al, 2001.	Gebhardt et al, 2001
Cost of Capital (Ohlson and Juettner-Nauroth, 2005)	The firm's cost of capital based on Ohlson and Juettner-Nauroth, 2005.	Ohlson and Juettner-Nauroth, 2005
Dummy variable *Segment 1*	Dummy variable that is equal to 1 if the firm has sales in only a single product market segment.	Compustat Segments
Dummy variable *Segment 2*	Dummy variable that is equal to 1 if the firm has sales in exactly two product market segments.	Compustat Segments
Dummy variable *Segment 3*	Dummy variable that is equal to 1 if the firm has sales in exactly three product market segments.	Compustat Segments
Dummy variable *Segment 4*	Dummy variable that is equal to 1 if the firm has sales in more than four product market segments.	Compustat Segments

Earnings Coef. of Variation	Earnings Coefficient of Variation that is the standard deviation of the firm's earnings divided by average earnings over the last 3 years.	Compustat
Industry Centroid	Industry Centroid Technology Uniqueness measure based on a 6-digit GICS industry classification.	KPSS2017
Intangible Assets	The ratio of intangible assets to total assets.	Compustat
Knowledge Spillover Shock (non-standardized)	Dollar value of patent shocks by peers in commonly cited technology classes	KPSS2017
Market-Book	The ratio of the market value of equity to book value of equity for the firm.	Compustat
Number of firms in industry	Number of firms in the 6-digit GICS industry.	Compustat
Number of Shareholders (log)	Natural log of the number of outstanding shares.	Compustat
Profitability	The ratio of operating income before depreciation, minus total interest and income taxes, to total assets.	Compustat
Product Market Uniqueness	Normalized distance from the average industry business-segment portfolio.	Litov et al, 2012
R&D Intensity	The ratio of the firm's R&D expenditure to total operating expense.	Compustat
Return	Annual stock return for the fiscal year.	CRSP
ROA	The ratio of the firm's income before extraordinary items to total assets.	Compustat
Sales ($) (log)	Natural log of the firm's sales.	Compustat
Sales Growth (1-year)	The growth of the firm's sales over the past year.	Compustat
Sales Growth (past three years)	The growth of the firm's sales over the past three years.	Compustat
Share of Self-Citations	Share of new patents citing the firm’s own prior patents among all citations that year.	Wang et al, 2009
Share Turnover (log)	Total shares traded in the year divided by shares outstanding.	Compustat
Technological HHI	Firm level Technological concentration measure	KPSS2017
Technology Uniqueness (standardized)	Technological uniqueness computed using patent shares, standardized based on the 30 closest Hoberg–Phillips competitors each year.	Kogan et al (2017), Hoberg and Philips (2016)
Tobin's Q	The ratio of the firm's market value of assets to book value of assets.	Compustat
Volatility	Standard deviation of the firm's stock price.	CRSP

Appendix A2: Different Industry Classifications

In the main text, our baseline technological uniqueness measure is computed by using the 30 closest competitors – also called the "competitive set" – for each firm, based on 10-K business descriptions, as measured by Hoberg and Phillips (2016). However, this firm-specific competitive set is allowed to change from year-to-year based on changes in product and business descriptions in 10-K filings. An alternative approach to define competitors was pursued by us in earlier draft versions, using traditional industry classifications. This approach comes at the disadvantage of relying on more aggregated and therefore often less precise classification of firms into industries. At the same time, traditional industry classifications are by definition static and therefore tend to fix the set of competing firms.

Table A2 recalculates technological uniqueness using either 4-digit industries of the Global Industry Classification System (GICS) or 4-digit SIC codes from the US. We find qualitatively and quantitatively similar results, even if standard errors tend to be larger, as one would expect if static industry classifications tend to be more noisy than the firm-specific competitive sets.

Table A02: Technological Uniqueness and Industry Categories

Panel A. GROUP (4-GICS)	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
Models	(1)	(2)	(3)	(4)
TU GROUP	0.0252***	0.0584**	0.00716***	0.00774***
	(0.00611)	(0.0257)	(0.00238)	(0.00264)
R-squared	0.0742	0.0614	0.197	0.133
Observations	23026	23026	23026	23026

Panel B. SIC (4-Digit)	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
Models	(1)	(2)	(3)	(4)
TU SIC4	0.0522**	0.0753	0.0173**	0.0146*
	(0.0208)	(0.0768)	(0.00777)	(0.00866)
R-squared	0.0786	0.0600	0.216	0.144
Observations	18,698	18,698	18,698	18,698

Notes: Technological uniqueness is measured as the normalized distance from the average industry patent portfolio. Industries are constructed by using the Global Industry Classification (GICS) and SIC classification system. Panel A defines industries at the 4-digit GICS level (GGROUP). Panel B defines industries at the 4-digit SIC level. All regressions include firm, location, industry, and year fixed effects. The sample is restricted to patenting firms, and controls are identical to those in Table 2 of the main text. Standard errors are clustered at the firm level and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A3: Disaggregation Level of Patent Classes used for Technological Uniqueness

Because a firm's measured technological uniqueness may depend on how technology classes are defined, we perform an additional robustness check by redefining patent technology classes based on the first four alphanumeric digits of the patent's CPC, rather than the baseline definition that uses the first three. This finer classification increases the number of distinct technology classes from 129 to 665.

In Table A3, we show that this alternative patent class decomposition has no qualitative impact on our OLS performance results.

Table A03: Technological Uniqueness and Patent Class Aggregation

Panel A. Patent Section	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**

Models	(1)	(2)	(3)	(4)
Technological Uniqueness (CPC Section)	0.0142***	0.0511***	0.00224	0.00226
	(0.00509)	(0.0167)	(0.00191)	(0.00208)
R-squared	0.0855	0.0593	0.219	0.149
Observations	19536	19536	19536	19536

Panel B. Patent Class (baseline)	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
Models	(1)	(2)	(3)	(4)
Technological Uniqueness (CPC Class)	0.0227***	0.0821***	0.00469**	0.00480*
	(0.00618)	(0.0238)	(0.00223)	(0.00254)
R-squared	0.0861	0.0601	0.219	0.149
Observations	19536	19536	19536	19536

Panel C. Patent (subclass)	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
Models	(1)	(2)	(3)	(4)
Technological Uniqueness (CPC Subclass)	0.0215***	0.0943***	0.00438*	0.00378
	(0.00655)	(0.0267)	(0.00234)	(0.00268)
R-squared	0.0860	0.0605	0.219	0.149
Observations	19536	19536	19536	19536

Notes: Technological Uniqueness is measured as the normalized distance between a firm's patent portfolio and the average patent portfolio of its Hoberg–Phillips (HP) product-market industry, define using each firm's 30 most product-similar peers (HP30). Patent technology classes are defined at section, class, and subclass levels. All regressions include firm, location, industry, and year fixed effects. The sample is restricted to patenting firms, and controls are identical to those in Table 2 of the main text. Standard errors are clustered at the firm level and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A4: Patent Class Weighting – Detailed Example

Since Jan 1st, 2013, the USPTO began transitioning from the United States Patent Classification (USPC) system to the Cooperative Patent Classification (CPC) system, a joint effort by the European Patent Office (EPO) and USPTO to "harmonize" their classification systems into a single hierarchal system having similar structure to the International Patent Classification (IPC). By 2015, the USPTO was exclusively classifying using the CPC system only and the USPC classes were no longer being updated.[1]

The stated goal of the CPC system is to accurately classify patents, facilitating the retrieval of their technical subject matter[2] and does so using a hierarchical level organizing and naming system.[3] Table A4 Panel A is an example of a patent (#7877944) that was granted to a firm in 2011. We assign the patent to a technology class using the patent's section and class designation, or the first three alpha-numeric values of the CPC. Starting with the section designation (A, B, C, D, E, F, G, H, and Y), there are eight main trunk assignments possible (A-H), with an additional section Y reserved for new emerging and/or cross-sectional technologies. The next two digits in the CPC system determines the class assignment. For instance, from Table 1 in the main text, patent technology class F41 includes all mechanical engineering patents (section F) related to weapons and weapons-related components (class 41). In contrast, technology class F42 encompasses mechanical engineering patents (section F) specifically related to ammunition and blasting (class 42).

Table A4: Patent Class Weighting Examples

Panel A: Patent Example

[1] See https://e-courses.epo.org/mod/url/view.php?id=916

[2] See https://www.uspto.gov/web/offices/pac/mpep/s905.html

[3] The CPC system classifies patents by Section-> Class -> Subclass -> Groups -> Subgroups.

United States Patent	**7,877,944**
Seidel	**February 1, 2011**

Tower foundation, in particular for a wind energy turbine

Abstract

A tower, in particular for a wind energy turbine, comprises a first tower segment (18) having a wall (20) comprising concrete material and a second tower segment (26) having a wall (28) comprising steel. The wall (28) of the second tower segment (26) comprises an end portion (30) embedded in an embedent portion (32) of the wall (20) of the first tower segment (18). The second tower segment (26) within its embedded end portion (30) comprises at least one anchoring element (38, 40, 52) projecting radially from an inner or an outer surface (42, 44) or both inner and outer surfaces (42, 44) of the wall (28) of the second tower segment (26), the anchoring elements (38, 40, 52) being arranged along an axial direction of the second tower segment (26).

Panel B: Cooperative Patenting Classification (CPC) and Technology Classes

Patent Number	**CPCs**	**Kogan et al (2017)**	**Equal Weight**	**Weighted Classes**	**Majority Class**	**First Class (Kogan)**
7877944	E02D 27/42; F03D 13/22; F05B 2230/60; Y02E 10/728; Y02E 10/72; Y02P 70/50; F05B 2240/912	E02D27/42;F03D11/045;F03D13/22;F05B2230/60;F05B2240/912;Y02E10/728;Y02P70/523	E02, F03, F05, Y02	E02 (0.14), F03 (0.29), F05 (0.29) , Y02(0.29)	F03 (0.33), F05 (0.33), Y02 (0.33)	E02
7328707	A61B 17/00234; A61B 17/12022; A61B 17/3468; A61F 5/0079; A61B 2017/00557; A61B 2017/00827; A61F 2/0036; A61F 2/20; Y10S 128/25	A61B17/00234;A61B17/12022;A61B17/3468;A61B2017/00557;A61B2017/00827;A61F2/0036;A61F2/20;A61F5/0079;Y10S128/25	A61, Y10	A61 (0.89), Y10(0.11)	A61	A61
8477817	H01S 5/12; B82Y 20/00; H01S 5/34306 ; H01S 5/1231; H01S 5/3406; H01S 5/209	B82Y20/00;H01S5/12;H01S5/1231;H01S5/209;H01S5/3406;H01S5/34306	B82, H01	B82 (0.17), H01 (0.83)	H01 (5)	B82
7059778	G02B 6/4298; G03F 7/70166; G03F 7/70075; G02B 6/06; B82Y 10/00 ; G02B 6/4249; Y10S 385/901	B82Y10/00;G02B6/06;G02B6/4249;G02B6/4298;G03F7/70075;G03F7/70166;Y10S385/901	B82, G02, G03, Y10	B82 (0.14), G02 (0.43), G03 (0.29), Y10 (0.14)	G02 (3)	B82

One issue with the new CPC system of classifying patents is that each patent can be assigned to multiple CPC designations. Our technology class definition, based on the section-class hierarchy, reduces many of these multiples, as patents with different subclasses or subgroups can still share the same section and class assignment. In our sample, using our technology class hierarchy system, approximately 60% of the patents only have one technology class assignment. This effectively means that regardless of how we classify patents with multiple CPC designations, the majority of the patents in our sample will still be unaffected by this decision. However, the remaining 40% of the patents have two or more assigned technology classes, with the mean/median number of technology classes per patent equal to two.[4] In the following below, we will detail how we handle patents with multiple CPC designations.

Our patent CPC data comes from Kogan et al. (2017) (henceforth Kogan), who initially provided patent class data up to 2013 but has since extended coverage through 2020.[5] They scrape the patent's entire CPC data but their algorithm assembles the technology classes in alphabetical order, resulting in the loss of the ordering information after aggregating to our section-class hierarchy. For instance, consider patent 8988776 granted to 3M in 2015.[6] This patent involves multilayer optical films orientated in specific directions to reflect and transmit light. By our technology class definition, this patent is assigned to the following technology classes: G02, B32, and Y10. Technology class G02 encompasses technological systems involving optics, B32 involves layered products, and Y10 includes new technologies of multi-layered products of different thicknesses. Using the Kogan dataset, B32 is presented as the first technology class as it is ordered first alphabetically, in contrast to Justia[7] or Google Patents[8] who lists G02 first, according to the original patent image. This can present a problem when using the

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[4] This CPC distribution is highly skewed though (max number of different tech classes for a patent is 24), 88% of the patents have 2 or less technology classes using the section-class classification system.

[5] See https://github.com/KPSS2017/Technological-Innovation-Resource-Allocation-and-Growth-Extended-Data

[6] https://patft.uspto.gov/netacgi/nph-Parser?Sect1=PTO1&Sect2=HITOFF&d=PALL&p=1&u=%2Fnetahtml%2FPTO%2Fsrchnum.htm&r=1&f=G&l=50&s1=8988776.PN.&OS=PN/8988776&RS=PN/8988776

[7] https://patents.justia.com/patent/8988776

[8] https://patents.google.com/patent/US8988776

Kogan dataset if the patent has multiple technology class designations and the researcher only uses the first class in the Kogan dataset. While the first class in the Kogan dataset is still a class based on a CPC assigned to the patent, it may not be the primary class as determined by the USPTO, and assuming it is may induce measurement error in the results.

Before we detail how we address the multiple CPC issue, it is worth mentioning again that this only affects 40% of patents in the sample, as the remaining 60% of patents are categorized into one technology class. The first method of categorizing patents, as presented in the main text, employs an equal weighting scheme, assuming that all technology classes receive the same weight and are equally represented, regardless of how the CPCs are ordered. The drawback to this scheme, however, is that it ignores patents with multiple classifications into the same technology class. Yet, since all technology classes are equally weighted, this reduces the likelihood of mis-categorizing the primary technology class of the patent. In Table A4 Panel B, each of the patents listed in column 1 is assigned an equal weight into the technology classes listed in column 4. This method results in no difference between using the actual CPC data and that obtained from Kogan. Consider the example of patent number 7877944 (Table A4 panel B row 2). When equal weighting is applied to the CPCs, each of the four technology classes (F02, F03, F05, and Y02) is given an equal weight of 0.25.

Appendix A5: Different Weighting Schemes for Patents with Multiple Patent Classes for Technological Uniqueness Measure

Next, we consider different weighting algorithms to factor in patents that are assigned to multiple technology classes. In Table A04 column 5 (weighted-classes), each patent is normalized by the total number of assigned technology classes, ensuring that the sum of the weights of the technology classes for each patent always adds up to 1. For patent number 7328707 in row 2 of Table A4 panel B, technology class A61 appears 8 times while Y10 appears only once. Under the weighted-class algorithm, A61 is given a technology class weight of 0.89 (8/9) while Y10 is given a technology class weight of 0.11 (1/9).

The majority class records the technology class occurs with the highest frequency. In cases where patents have multiple technology class assignments that occur with the same frequency, an equal weighting algorithm is applied. For example, in Table A4 Panel B, patent number 8477817 has technology class H01 occurring in the assigned CPCs and is thus designated as the assigned technology class.

Finally, the first-class approach is the first technology class assigned in the Kogan dataset. While this approach may incorrectly assume that a secondary technology class is the primary technology class, as observed in Table A4 Panel B for patents 8477817 and 7059778, our informal examinations indicate that this first-class approach still correctly selects the primary class 80% of the time.[9] Table A5 provides an example of how the four different measures compare.

Table A05: Comparison of Alternative Patent Class Decompositions

Panel A: Patent Classes (Class-Weighted)

	Sales Growth	**Tobin's Q**	**Profitability**	**ROA**
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technology Uniqueness	0.0225***	0.0638***	0.00159	0.00107
	(0.00558)	(0.0210)	(0.00193)	(0.00221)
Additional Controls	See Table Notes			
Fixed Effects	Firm, Location, Industry, Year			
R2	0.0852	0.0595	0.219	0.149
Observations	19,536	19,536	19,536	19,536

Panel B: Patent Classes (Majority Class)

[9] This includes the 60% of all patents that has one technology class.

	Sales Growth	Tobin's Q	Profitability	ROA
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technology Uniqueness (HP30)	0.0240***	0.0928***	0.00513**	0.00506**
	(0.00609)	(0.0234)	(0.00220)	(0.00249)
Additional Controls	See Table Notes			
Fixed Effects	Firm, Location, Industry, Year			
R2	0.0864	0.0607	0.219	0.149
Observations	19,536	19,536	19,536	19,536

Panel C: Patent Classes (First Class)

	Sales Growth	Tobin's Q	Profitability	ROA
	OLS	OLS	OLS	OLS
Models	(1)	(2)	(3)	(4)
Technology Uniqueness (HP30)	0.0251***	0.0745***	0.00569**	0.00494*
	(0.00605)	(0.0244)	(0.00234)	(0.00271)
Additional Controls	See Table Notes			
Fixed Effects	Firm, Location, Industry, Year			
R2	0.0863	0.0598	0.219	0.149
Observations	19,536	19,536	19,536	19,536

Notes: Technological Uniqueness is measured as the normalized distance between a firm's patent portfolio and the average patent portfolio of its Hoberg–Phillips (HP) product-market industry, defined using each firm's 30 most product-similar peers (HP30). Patents are classified to the three-digit class by weighted frequency of three-digit classes in Panel A, assignment to the three-digit class that occurs the most frequently (majority) in Panel B, and assignment to the class that first appears in the Kogan et. al data set (first class) in Panel C. All regressions include firm, location, industry, and year fixed effects. The sample is restricted to patenting firms, and controls are identical to those in Table 2 of the main text. Standard errors are clustered at the firm level and are reported in parentheses. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A6: Different Rolling Windows for Technological Uniqueness Measure

Our baseline results apply a rolling three-year patent grant counting approach to minimize the impact of the uncertainty surrounding patent grants that are out of the firm's control. The choice of three-years is based on the median time it takes for a patent application to be granted in the sample. Shorter rolling periods may make firms appear more unique, as they decrease the impact of a more diverse set of patents in the firm's portfolio.

In Table A6, we apply a rolling five-year patent grant counting approach and find that our performance results continue to hold.

Table A06 Performance Metric Regressions: OLS only (Using 5-years of

	Sales Growth	Tobin's Q	Profitability	ROA
Models	(1)	(2)	(3)	(4)
Technology Uniqueness (HP30)	0.0238***	0.0831***	0.00502**	0.00621**
	(0.00654)	(0.0259)	(0.00232)	(0.00272)
Additional Controls	See table notes.			
Fixed effects	Firm, Location, Industry, Year			
Standard Errors	Clustered at the firm level			
R-squared	0.0860	0.0599	0.219	0.150

Observations	19,536	19,536	19,536	19,536

Notes: Technological Uniqueness is measured as the normalized distance between a firm's patent portfolio and the average patent portfolio of its Hoberg–Phillips (HP) product-market industry, define using each firm's 30 most product-similar peers (HP30). In this specification, we use the 5-year rollin granted patents to compute the firm's TU measure. All regressions include firm, location, industry, an year fixed effects. The sample is restricted to patenting firms, and controls are identical to those in Ta 2 of the main text. Standard errors are clustered at the firm level. Statistical significance levels: *: 10 **: 5%, ***: 1%.

Appendix A7: Different numbers of competitors in the "competitive set"

Our baseline results define the competitive set used to construct the TU measure as the 30 most similar firms based on the Hoberg Philips similarity measure. To ensure that this choice is not driving the results, we vary the number of peer firms used in defining the competitive set from 5 to 100.

As shown in Table A7, our results remain robust across alternative definitions. The effect of TU on firm performance continues to be positive and statistically significant, and its magnitude generally increases with larger peer sets, suggesting that differentiation becomes more salient when evaluated within a broader pool of technological competitors.

Table A07 Different number of competitors in the "competitive set"

	Sales Growth	Tobin's Q	Profitability	ROA
Models	(1)	(2)	(3)	(4)
TU (5HP)	0.0132***	0.0457***	0.000796	0.000897
	(0.00448)	(0.0176)	(0.00170)	(0.00200)
TU (20HP)	0.0196***	0.0797***	0.00317	0.00320
	(0.00582)	(0.0224)	(0.00215)	(0.00247)
TU(30HP Baseline)	0.0227***	0.0821***	0.00469**	0.00480*
	(0.00618)	(0.0238)	(0.00223)	(0.00254)
TU (50HP)	0.0281***	0.0874***	0.00549**	0.00636**

	(0.00668)	(0.0258)	(0.00248)	(0.00277)
TU (75HP)	0.0266***	0.0919***	0.00505*	0.00596**
	(0.00694)	(0.0271)	(0.00262)	(0.00290)
TU (100HP)	0.0272***	0.0909***	0.00581**	0.00684**
	(0.00720)	(0.0279)	(0.00270)	(0.00300)

Notes: Technological Uniqueness is measured as the normalized distance from the average industry patent portfolio. Industries are defined using the Hoberg–Phillips product market similarity scores, based on each firm's most similar competitors in a given year. In this specification, we vary the number of peer firms in the competitive set from 5 to 100. All regressions include firm, location, industry, and year fixed effects. The sample is restricted to patenting firms, and controls are identical to those in Table 2 of the main text. Standard errors are clustered at the firm level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A8: Discussion on how the TU measure differs from the TD measure

Our measure of Technological Uniqueness (TU) differs empirically from the Technological Differentiation (TD) measure developed by Arts, Veugelers, and Cassiman (2021). Both approaches rely on cosine similarity measures to quantify technological differentiation but emphasize different sources of variation in firms' technological positions.

Technological Differentiation: Arts et al. (2021)

The technological differentiation measure developed by Arts et al. captures how distinct a firm's patent portfolio is relative to its closest peers in technological space. Specifically, Arts et al. compute patent-text vectors for patenting firms and pairwise cosine similarities are computed between firms within the same year. For each firm, the average cosine similarity with its top decile of most similar peers is calculated and then used to obtain the differentiation score. Hence, technological differentiation captures absolute differentiation in technological space, not within an industry-defined local neighborhood.

Arts et al. also report alternative specifications of the measure based on the scope of the comparison set (e.g. the top 1%, top 5%, or all peers) when computing the average similarity. These versions differ in the locality of the benchmark. The top 1% and top 5% measures emphasize differentiation from the most similar technological neighbors, while the all-peers version captures distance from the overall technological center of gravity. Comparing these versions allows the authors to test whether firm outcomes are more closely associated with local distinctiveness—standing out from nearby technologies—or with global novelty.

Technological Uniqueness: (This Paper)

In contrast, our technological uniqueness measure is computed as the normalized distance between a firm's patent vector and the mean industry vector, based on Hoberg–Phillips (HP) product-market industry definitions. This measure captures how far a firm's technology portfolio is from the average technology portfolio of the entire industry rather than from its most similar peers.

This industry-centered approach emphasizes strategic differentiation at the industry level, highlighting firms that occupy technological niches unaddressed by typical competitors, rather than simply those that are dissimilar to their closest technological neighbors.

Hence, our TU measure is potentially better at studying the strategic benefits of deviating from industry norms or crowding as a relative positioning measure. The TD measure can be better as capturing more radical or exploratory innovation that departs from established technological regimes as an absolute novelty measure.

In the main paper, we compare our TU measure to the "all peers" version of the TD measure as this version of the TD measure is the one that Arts et al emphasizes. However, as reported in Table A08 Panel A, we find that the correlation between the various TD measures is very high, ranging from 0.93 to 0.99 while the correlation of the TU measure to the TD measures ranges from 0.32 to 0.36.

An important distinction between emphasizing absolute differentiation and localized differentiation within an industry lies in the firm's ability to sustain its uniqueness advantage over time. As shown in Table A8, Panels B and C, both TU and exhibit substantial serial correlation, indicating that firms' technological positions are persistent. However, the TD measures display notably higher autocorrelations, remaining above 0.90 even at a four-year lag, suggesting that firms differentiated from the broader technological landscape tend to maintain their differentiation for longer periods. In contrast, TU exhibits somewhat lower persistence, consistent with the idea that industry-relative differentiation may evolve more rapidly as firms adapt to shifting competitive and technological conditions. This difference in autocorrelations makes it more likely that the TD measure is more sensitive to the use firm fixed effects in empirical specifications.

Table A08 Comparison between TD and TU Measures

Panel A:

Variables	TU	TD (Top 10%)	TD (Top 5%)	TD (Top 1%)	TD (all)
TU	1				
TD (Top 10%)	0.318	1			
TD (Top 5%)	0.325	0.999	1		
TD (Top 1%)	0.364	0.954	0.961	1	
TD (all)	0.321	0.989	0.983	0.93	1

Panel B

Variables	**TU**	**TU (t-1)**	**TU (t-2)**	**TU (t-3)**	**TU (t-4)**
TU	1				
TU (t-1)	0.882	1			
TU (t-2)	0.817	0.879	1		
TU (t-3)	0.758	0.81	0.878	1	
TU (t-4)	0.724	0.751	0.811	0.875	1

Panel C

Variables	TD	TD (t-1)	TD (t-2)	TD (t-3)	TD (t-4)
TD	1				
TD (t-1)	0.978	1			
TD (t-2)	0.949	0.978	1		
TD (t-3)	0.914	0.949	0.978	1	
TD (t-4)	0.875	0.912	0.947	0.976	1

Notes: Technological Uniqueness (TU) is measured as the normalized distance between a firm's patent portfolio and the average patent portfolio of its Hoberg–Phillips (HP) product-market industry, defined using each firm's 30 most product-similar peers (HP30). Technological Differentiation (TD) follows Arts, Cassiman, and Hou (2023) and is measured as the average normalized distance between a firm's patent vector and those of other patenting firms. Alternative versions of the TD measure are based on the comparison set used to compute average similarity, using either the top 1%, top 5%, or all peers. Panel A reports cross-sectional correlations between TU and alternative TD measures; Panel B reports serial correlations of TU; and Panel C reports serial correlations of the TD (all-peers) specification. The sample is restricted to firms with at least one granted patent.

Appendix A9: Results – Different Types of Fixed Effects

Our baseline OLS specification includes firm, industry, region, year fixed effects, along with a full set of control variables to account for both observable and unobservable heterogeneity. To assess the sensitivity of our results to the inclusion of these fixed effects, we re-estimate the baseline models using alternative fixed-effect structures and without controls.

As reported in Table A9, the positive association between TU and firm performance remains robust when using simpler specifications that include only firm and year fixed effects, with or without controls. In our empirical analysis, we found that firm fixed effects are required as a minimum set of controls to remove selection effects that may bias the OLS results.

Overall, these results indicate that our conclusions are not sensitive to the choice of fixed-effect specification.

Table A09: Technological Uniqueness and Firm Performance with different fixed

	Sales Growth	**Tobin's Q**	**Profitability**	**ROA**
Models	(1)	(2)	(3)	(4)
Technology Uniqueness (HP30)	0.0144***	0.0864***	0.00322	0.00426
(no controls, firm, gind, region, year FE)	(0.00511)	(0.0232)	(0.00245)	(0.00269)
Technology Uniqueness (HP30)	0.0151***	0.0911***	0.00297	0.00387
(no controls, firm, year FE)	(0.00512)	(0.0235)	(0.00245)	(0.00270)
Technology Uniqueness (HP30)	0.0238***	0.0843***	0.00470**	0.00471*
(all controls, firm, year FE)	(0.00617)	(0.0240)	(0.00222)	(0.00255)

Notes: Technological Uniqueness (TU) is measured as the normalized distance between a firm's pater portfolio and the average patent portfolio of its Hoberg–Phillips (HP) product-market industry, define using each firm's 30 most product-similar peers (HP30). The estimates of the OLS model presented a (1) no controls but the full set of fixed effects, (2) no controls but only firm and year fixed effects, (3) controls and only firm and year fixed effects, and (4) all controls, firm and year fixed effects using the between-estimator. The sample is restricted to patenting firms only. Standard errors are clustered at th level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A10: Detailed Discussion of Instrumental Variables Approaches

A10.1 Industry Centroid IV

The first instrumental variable is based on changes in the average patenting portfolio of firms in the industry ("industry centroid") and is therefore referred to as "Centroid IV". The key idea of this IV is as follows: when companies in the same industry pursue similar technology trends, they inadvertently leave unaddressed niches, which create opportunities. A focal firm can stand out by specializing in these technological niche areas and, therefore, more easily create a unique technology portfolio. For example, in the early 2000s, major cellphone manufacturers such as Nokia and Research-in-Motion, which produced the "Blackberry", focused on technologies surrounding 3-G call quality, GPS, phone battery life, message encryption, and keyboard quality. Apple's iPhone, introduced in 2007, lagged behind in all those dimensions but had the unique feature of a touchscreen, which ended up becoming the dominant design feature. We construct a shift-share (or "Bartik" style) IV, based on the idea that firms in technology locations with high local clustering with other firms in the same industry will pay more attention to industry centroid changes. The first stage of our IV estimator is given by:

$$TU_{i,t} = \gamma \cdot Z_{i,t} + controls_{i,t} + D_i + D_s \times D_t + D_l \times D_t + e_{i,t} \qquad \text{(A10.1)}$$

Where $Z_{i,t} = s_{s,l} \times \Delta C_{s,t-1}$ is the instrument, with $s_{s,l}$ as initial industry shares in terms of revenue in location l and $\Delta C_{s,t-1}$ as lagged changes in the "leave-out-mean" (or "Hausman-IV") industry patenting centroids. As we discuss below, we use leave-out-means to purge out any direct effects of changes in patenting of the focal firm, which might lead to a mechanical correlation between our IV and technological uniqueness. The combination of exogenous industry-level shocks and local exposure shares have recently been widely used in applied econometric work, see Borusyak et al. (2022). Importantly, the use of the shift-share IV allows us to add a full set of industry-by-year fixed effects $D_s \times D_t$ and location-by-year fixed effects $D_l \times D_t$, as the identifying variation in the first (A10.1) and the second stage (A10.2) estimates, as the IV estimation relies on the interaction of industry shocks and local cross-sectional variation.

The second stage is given by:

$$y_{i,t} = \beta \cdot \hat{TU}_{i,t} + controls_{i,t} + D_i + D_s \times D_t + D_l \times D_t + \epsilon_{i,t} \tag{A10.2}$$

$\hat{TU}_{i,t}$ are conceptually the predicted values from the first stage, even though we estimate (A10.1) and (A10.2) simultaneously.

This IV has several advantages. First, leave-out-mean centroid changes directly address reverse causality, since these changes by construction, omit the focal firm. At the same time, lagged centroid changes reflect patenting by a firm's industry rivals and therefore generate an incentive by the focal firm to respond. Finally, since local industry clustering is more likely to be exogenous, a shift-share style IV should provide more robust estimates, with the additional advantage that we are able to include a full set of industry-by-year fixed effects.

Second, we retain a full set of firm fixed effects, thereby allowing us to focus on the within-firm patenting response to exogenous changes in the industry patent portfolio. This helps to address selection bias on permanent unobservables. Third, our IV strategy is also attractive in the context of the necessary IV exclusion restriction. To understand this, let us fix ideas by denoting with $\tilde{x}$ any variable x, from which we removed the impact of the control variables and fixed effects listed under (A10.1) and (A10.2). Then, the IV estimate can be written as:

$$\hat{\beta}_{IV} = \beta + \frac{Cov\left(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}\right)}{Cov\left(\tilde{TU}_{i,t}, \tilde{Z}_{s,t}\right)} \tag{A10.3}$$

with $Cov\left(\tilde{TU}_{i,t}, \tilde{Z}_{s,t}\right) > 0$, as the first stage will establish that industry centroid changes increase uniqueness at the focal firm. The IV estimate will be biased towards finding that more technological uniqueness increases firm performance if $Cov\left(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}\right) > 0$. However, this is unlikely, since our shift-share Centroid-IV is a leave-out-mean, which means $\tilde{Z}_{s,t}$ only reflects changes in technology trends at competing firms. In turn, competitors in an industry will only patent technologies they anticipate to be profit-maximizing, which should (weakly) reduce profits at the focal firm. In other words, if competitors in the industry only patent technologies that they believe will increase their own profits, then it should be true that $Cov\left(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}\right) \leq 0$, which will lead to an underestimate of the true causal performance effect of technological uniqueness.

A10.2 Patent Expiration IV

Our second IV is based on industry-level patent expiration shocks. The key idea of this empirical approach is that if many patents in the industry expire mandatorily, this will tend to reduce technological uniqueness at a focal firm, since it is now legally allowed to use technologies with mandatorily expired patents for its upcoming inventions. As mentioned in the main text, this allows us to estimate a different type of causal performance effect of technological uniqueness. The Centroid-IV estimates the positive performance effects of technological uniqueness: more technological uniqueness causes firms to raise performance.

However, it is theoretically possible for less technologically unique firms to stagnate in terms of performance instead of performing worse. As in the case of the Centroid-IV, we construct the Patent Expiration IV using a leave-out-mean, which facilitates identification, as discussed below. As in the case of R&D Tax Credits, this Patent Expiration IV will estimate negative performance effects of technological uniqueness, as we expect less technologically unique firms to perform worse.

For each year for each industry *s,* we compute a vector of expiring patent-shares across all technology classes based on the prior patents granted to peer firms 18 or 20 years ago.[10] These expiring patent shares are then used to construct a Bartik-style IVs by multiplying them with firm-level variables that measure the initial distribution of patents a firm has across technology classes. This shift-share approach postulates that patent expirations should be more important for a focal firm if it uses the technology classes in which the patents expire more. The first stage of this IV approach is given by:

$$TU_{i,t} = \gamma \cdot Z_{i,t} + controls_{i,t} + D_i + D_s + D_l + D_t + e_{i,t} \tag{A10.4}$$

With $Z_{i,t} = P_{s,0} \times \Delta P_{s,t}$, where $P_{s,0}$ is the initial industry-level patent granted shares and $\Delta P_{s,t}$ is the annual vector of expiring patents. As we discussed, we expect that $\gamma < 0$, since more patent expirations should lead to less technological uniqueness as all firms in an industry have free access to technology with expired patents. The predicted technological uniqueness from (A10.4) is then used to predict firm performance, as before.

[10] In 1994, the United States enacted the Uruguay Round Agreements Act which changed the patent term from based on the grant date of the patent to the application date of the patent. For patents with application dates after June 7, 1995, their patent terms last 20 years from the application date. This is the definition that we use to determine when patents expire.

$$y_{i,t} = \beta \cdot \hat{TU}_{i,t} + controls_{i,t} + D_i + D_s + D_l + D_t + \epsilon_{i,t}$$

(A10.5)

As in the context of the R&D Tax Credits, our prediction is that $\beta > 0$, because firms with less technological uniqueness will tend to perform worse.

There are at least two ways the exclusion restriction for the Patent Expiration IV might fail. On the one hand, the timing of patent expirations might be correlated with technological or growth opportunities. However, such a correlation is unlikely, since patents expire 20 years after they are being granted. For industry-wide patent expirations to be correlated with current technological or competitive conditions, firms would need to accurately forecast technological or industry forces 20 years into the future. We believe that accurate forecasts over such long horizons are implausible.

On the other hand, patent expirations imply that intellectual property rights mandatorily expire, which might directly impact profits. To further understand the threat to the exclusion restriction criterion, we again denote with $\tilde{x}$ any variable x, from which we removed the impact of the control variables and fixed effects listed under (3) and (4). The IV estimator can therefore be written as

$$\hat{\beta}_{IV} = \beta + \frac{Cov\left(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}\right)}{Cov\left(\tilde{TU}_{i,t}, \tilde{Z}_{s,t}\right)} \quad \text{(A10.6)}$$

Since $Cov\left(\tilde{TU}_{i,t}, \tilde{Z}_{s,t}\right) < 0$ for the Patent Expiration IV, the IV estimator will only be biased towards a positive coefficient if $Cov\left(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}\right) < 0$, i.e., more industry patent expirations reduce profits. However, the Patent Expiration IV is constructed as a leave-out-mean, which means that the patent expiration of the focal firm is not included. At the same time, patent expirations at competitors will tend to increase performance at the focal firm, which would imply $Cov\left(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}\right) \geq 0$, which suggests that our IV strategy likely underestimates the true causal effect.

A10.3 R&D Tax Credit IV

Our second identification strategy is based on state-level changes in R&D tax credits. This exogenous variation has previously been used by Bloom et al. (2013), but we utilize it in a novel way. Specifically, we hypothesize that higher R&D tax credits will incentivize firms to increase R&D spending on marginal innovations instead of radical innovations, since these are easier to obtain and will still earn the tax deductions from the R&D tax credits. Such marginal innovations in turn are by definition very similar to already existing patented technologies and will therefore tend to reduce firms' technological uniqueness. Like the Patent Expiration IV, the R&D tax credit allows us to test whether there are negative performance effects of less technological performance: firms that reduce their technological uniqueness consequently perform worse.

We follow Bloom et al. (2013) and construct exogenous R&D capital stocks using exogenous changes to federal and state-level R&D tax credits:

$$Z_{i,t} = \beta_0 + \beta_1 * \log\left(FTC_{i,t}\right) + \beta_2 \log\left(STC_{i,t}\right) + D_i + D_s + D_l \qquad \text{(A10.7)}$$

where $Z_{i,t}$ are (log) R&D expenditures of firm *i* at time *t* and $FTC_{i,t}$ and $STC_{i,t}$ are the Federal R&D and State R&D tax credits, based on the location (state) of the firm *i* at time *t*. We use firm fixed effects D_i, location fixed effects D_l and industry fixed effects D_s. We then use the exogenous R&D capital stock as an instrument to predict technological uniqueness:

$$TU_{i,t} = \gamma \cdot Z_{i,t} + controls_{i,t} + D_i + D_s + D_l + \epsilon_{i,t} \qquad \text{(A10.8)}$$

We expect that $\gamma < 0$, because R&D tax credits are likely to stimulate marginal innovations that mimic peers and reduce technological uniqueness. This prediction concerning how R&D tax credits affect technological uniqueness is novel and not recognized in the original work by Bloom et al. (2013). In the second stage, the predicted TU values are used as an IV for firm performance:

$$y_{i,t} = \beta \cdot \hat{TU}_{i,t} + controls_{i,t} + D_i + D_s + D_l + \epsilon_{i,t} \tag{A10.9}$$

Our prediction is that $\beta > 0$, which in the case of $\gamma < 0$ will only be true if firms with higher values of $Z_{i,t}$ have lower performance. To see this, define the reduced form as

$$y_{i,t} = \delta \cdot Z_{i,t} + controls_{i,t} + D_i + D_s + D_l + \epsilon_{i,t} \tag{A10.10}$$

Then it can be shown that:

$$\hat{\beta}_{IV} = \frac{\hat{\delta}}{\hat{\gamma}} \tag{A10.11}$$

In the case of the R&D Tax Credit IV, our prediction is that $\hat{\gamma} < 0$ so that $\hat{\beta}_{IV} > 0$ only if $\delta < 0$, which in turn means that firms with higher values of $Z_{i,t}$ tend to exhibit lower firm performance $y_{i,t}$.

Again, a critical question is whether the exclusion restriction holds and as before we base our discussion on equation (A10.3) with $\tilde{x}$ denoting any variable x, from which we removed the impact of the control variables and fixed effects listed under (A10.5) and (A10.6):

$$\hat{\beta}_{IV} = \beta + \frac{Cov\left(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}\right)}{Cov\left(\tilde{TU}_{i,t}, \tilde{Z}_{s,t}\right)} \tag{A10.12}$$

Where, due to the first stage, we expect $Cov\left(\tilde{TU}_{i,t}, \tilde{Z}_{s,t}\right) < 0$. Under this condition, the IV estimate will only overestimate the impact of technological uniqueness on firm performance if $Cov\left(\tilde{\epsilon}_{i,t}, \tilde{Z}_{s,t}\right) < 0$. In other words, tax-credit induced R&D needs to directly reduce firm performance to induce an upwards bias on our IV estimates. At the same time, the empirical findings in Bloom et al. (2013) have shown that exogenous R&D, in fact, tends to increase firm performance as measured by productivity and Tobin's Q. Therefore, our analysis suggests that if anything, IV estimates using R&D tax credits will tend to underestimate the effect of technological uniqueness on firm performance.

Appendix A11: Borusyak et al. (2025) checklist for Share-based identification in Bartik IVs

In this section we closely follow the discussion in (Borusyak et al, 2025) for our shift-share or Bartik IV. As extensively discussed in the recent econometrics literature on shift-share instruments (Goldsmith-Pinkham et al., 2020; Borusyak et al. 2020) identification in these IVs requires either exogeneity in the cross-sectional "share" variation (Goldsmith-Pinkham et al., 2020) or in the time series variation, also called "shifts" (Borusyak et al. 2020). We focus especially on the cross-sectional shares, since they offer a large degree of variation. (Borusyak et al, 2025) recommend a five-point "checklist" to build the case for a valid shift-share instrument based on cross-sectional shares being exogenous. First, explicating the identification arguments for why exposure shares are "suitable IVs". Second, add necessary unit-level controls if this can improve identification. Third, characterize which shares in the cross-section are driving effects, using Rotemberg weights discussed in (Borusyak et al. 2020). Fourth, provide balance tests documenting the plausible exogeneity of shares. And fifth provide over identification test statistics.

As necessary context for our discussion, we restate here the constriction of our main Centroid-IV, which can be formalized as

$$Z_{i,t} = s_{s,l} \times \Delta C_{s,t-1}$$

where, i, t, s index firms, time periods and industries, respectively. The variable $s_{s,l}$ measures the importance of industry s in location l at some initial point in time, measured as the share of industry s revenue of publicly traded firms in location l. This is the "share" variable for our IV. In contrast the variable $\Delta C_{s,t-1}$ measures the change in the (leave-out-mean) industry centroid of patented technologies, which is the "shift" variable for our IV. As we discuss in the main paper, the basic idea of our Centroid-IV is that common technological trends by competitors, as measured by $\Delta C_{s,t-1}$ potentially open up technological niches that focal firms are able to exploit to increase their technological uniqueness. At the same time, salience of common technology trends at competitors will be larger, the more competitors are located closely, as captured by the share $s_{s,l}$.

We begin with the conceptual suitability argument for why $s_{s,l}$ is plausibly a valid instrument. For an instrument to be valid, it needs to meet relevance and exclusion restrictions. From a theoretical perspective, the importance of the industry of the focal firm in its location is likely to make this focal firm much more aware of competitor's actions and technologies. This can be driven by indirect knowledge exchange by hiring employees away from competitors (Bloom et al., 2019) or by the relative ease of observing closely competitors directly. Given better observability of competitors' technologies, we hypothesize that such information will be directly informative in the decision of what types of technological resources to pursue at the focal firm — leading to relevance of the variable $s_{s,l}$ for technological uniqueness choices. As discussed by (Goldsmith-Pinkham et al., 2020) in a shift-share IV that relies primarily on the exogeneity of shares, the shifts primarily provide weights that affect the relevance of the instrument. This makes sense in the context of our application, where the shifts measure common technological trends among competitors of the focal firm. The stronger the common trends are, the more impact they will have on technological uniqueness choices at the focal firm, thereby making the instrument more relevant in the first stage. At the same time, for firms that have no other firms in the same location, unawareness of common technological industry trends might lead to missing opportunities of technological niches, leaving performance changes unaffected. At the same time, the variable $s_{s,l}$ is likely strongly driven by historical location decisions of public corporations, which are mostly unrelated with technological opportunities today. In other words, the historical importance of the focal firm's industry in its location $s_{s,l}$ is unlikely to have a direct effect on the focal firm's performance, except through its technological choices. In other words, the historical industry shares are plausibly meeting the exclusion restrictions for identification of causal estimates from IV (Angrist and Pischke, 2009). This discussion captures our basic rationale for the plausible exogeneity of the share-part, which is the first item on the checklist provided by (Borusyak et al, 2025). As can be seen in Table A11a below, varying shares to different pre-sample periods has no qualitative impact on our main centroid IV results presented in Table 3 of the main text.

Table A11a: Centroid IV with different share years

	Sales Growth	**Tobin's Q**	**Profitability**	**ROA**
Models	(1)	(2)	(3)	(4)
Technology Uniqueness (HP30)	0.384**	1.599**	0.0936**	0.0912*
(1985 Shares)	(0.178)	(0.654)	(0.042)	(0.051)

Technology Uniqueness (HP30)	0.390**	1.689**	0.0991**	0.0986*
(1986 Shares)	(0.178)	(0.668)	(0.042)	(0.052)
Technology Uniqueness (HP30)	0.390**	1.681**	0.102**	0.102*
(1987 Shares)	(0.182)	(0.676)	(0.042)	(0.053)
Technology Uniqueness (HP30)	0.400**	1.718**	0.103**	0.103*
(average 1985-1987 shares)	(0.182)	(0.679)	(0.043)	(0.053)
Technology Uniqueness (HP30)	0.397**	1.656**	0.0948**	0.0923*
(average 1980-1987 shares)	(0.176)	(0.641)	(0.041)	(0.051)

Notes: Technological Uniqueness (TU) is measured as the normalized distance between a firm's pate portfolio and the average patent portfolio of its Hoberg–Phillips (HP) product-market industry, define using each firm's 30 most product-similar peers (HP30). The estimates of the centroid (Bartik) IV model presented are with (1) 1985 state-revenue shares (2) 1986 state-revenue shares (3) 1987 state-revenue shares (4) average 1985-1987 state-revenue shares and (5) average 1980-1987 state-revenue shares. All regressions include firm, location, industry, and year fixed effects. The sample is restrictec to patenting firms, and controls are identical to those in Table 2 of the main text. Standard errors are clustered at firm-level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

One potential concern about the share $s_{s,l}$ as an instrument is that it may also capture agglomeration effects. Even if for historical reasons locations like Silicon Valley had a head start, this initial advantage might just become stronger over time, due to local knowledge spillovers and young and talented tech workers continuing to move to the area. As a result, high-performing tech company may choose to either start or re-locate to Silicon Valley, thereby leading to a sample selection of high-performance firms with the share $s_{s,l}$. One way to address this concern is to use firm fixed effects, which focus the analysis on changes within the same firms, thereby removing any variation resulting from a comparison across sample-selected vs non-sample selected firms. This constitutes the second item on the (Borusyak et al, 2025) checklist.

Third, following Goldsmith-Pinkham, Sorkin, and Swift (2020), we compute Rotemberg weights to examine which industry centroid shocks contribute most to the variation in our Centroid IV. Table A11b presents the resulting weights aggregated to the GICS industry level. The distribution of weights indicates that the shocks are only moderately concentrated, with the top five industries accounting for about 41 percent of the identifying variation. This suggests that the identification of the Centroid IV is not dominated by a few industries but is instead broadly distributed across multiple sectors.

Table A11b: Rotemberg Weights

GICS	Industry	Rotemberg Weights
452030	Electronic Equipment, Instruments & Components	0.111
101010	Energy Equipment & Services	0.087
201040	Electrical Equipment	0.076
452020	Technology Hardware, Storage & Peripherals	0.076
453010	Semiconductors & Semiconductor Equipment	0.059
452010	Communications Equipment	0.058
151010	Chemicals	0.057
451030	Software	0.045
252010	Household Durables	0.044
201060	Machinery	0.043
302020	Food Products	0.040
201010	Aerospace & Defense	0.031
253010	Hotels, Restaurants & Leisure	0.030
251010	Automobile Components	0.029
202010	Commercial Services & Supplies	0.029

Note: This table reports the Rotemberg weights from the industry-centroid instrumental-variable specification. Each weight measures the contribution of a given GICS industry's centroid shock to the overall identifying variation in the 2SLS estimate. The weights are aggregated to the industry level. The top 15 industry weights are displayed while there are 31 overall industries. The weights sum to one and indicate which industries most strongly influence the identification of the Centroid IV.

Fourth, although the exclusion restriction for our IV cannot be formally tested, (Borusyak et al, 2025) propose to use balance tests for shares as a plausibility test for exogeneity. The basic idea is that if the identifying variation in the shift-share instrument is quasi-random, then performance prior to an initial period should not systematically differ across groups that contribute more versus less to the identifying variation. In our context, this implies that firms in industries with larger Rotemberg weights, i.e. those driving most of the identifying variation in the Centroid IV, should not exhibit different pre-trends in performance relative to firms in other industries. Consistent with this, Table A11c shows that first differences in performance outcomes (sales growth, Tobin's Q, profitability, and ROA) are not statistically significantly different between firms in the top three Rotemberg-weighted industries and those in all other industries. This supports the quasi-common trends interpretation of share exogeneity emphasized by Borusyak et al. (2025).

Table A11c. Centroid IV Balance Test: Top Three Industries by Rotemberg Weight vs. All Others

	Top 3 Industries (Rotemberg Weight)			**All Other Industries**			
	obs	mean	Std. Dev.	obs	mean	Std. Dev.	**t-test**
Sales Growth	2,460	-0.0107	0.0071	16,835	-0.0138	0.0032	-0.3602
Tobin's Q	2,461	-0.0258	0.0171	16,856	-0.0323	0.0082	-0.2908
Profitability	2,460	-0.0014	0.0017	16,863	0.0009	0.0008	1.0070

ROA	2,460	-0.0025	0.0023	16,863	0.0008	0.0011	1.1028

Notes: This table reports balance tests comparing firm performance between the top three industries with the highest Rotemberg weights and all other industries in the Centroid IV construction. The Rotemberg weights capture each industry's relative contribution to the overall identifying variation in the instrument. The performance variables—sales growth, Tobin's Q, profitability, and ROA—are averaged within each group. The reported t-statistics test whether mean performance differs significantly between firms in the top three weighted industries and those in all other industries.

Fifth, if the researchers are willing to assume that the causal effects are the same across all treated units, (Borusyak et al, 2025) recommend the use of traditional IV over identification tests, such as the Sargan-Hansen test statistic to diagnose whether any of the instruments are potentially endogenous. They write: "When the effects are homogeneous, the failure of the above tests indicates that the share exogeneity assumption is violated. This need not be the case with heterogeneous effects, as different combinations of share instruments may estimate different combinations of causal effects even when all share instruments are exogenous." As we extensively discuss on the text and the appendix, there is good reason to believe that treatment effects of technological uniqueness differ across firms (Porter and Siggelkow, 2008). This is exactly why we are carefully characterizing compliers in Appendix A14.

Appendix A12: Results of R&D Tax Credit IV

In Table A12 we report the results of using the R&D tax credit IV. This instrument exploits annual changes in state R&D tax credit policies as exogenous shocks to firms' R&D spending. The results are qualitatively consistent with the findings of the two natural experiments we report in the main text of the paper. However, the magnitudes are many times larger than the causal estimates reported in the paper. Future research might investigate why this particular natural experiment yields such large magnitudes.

Table A12: Causal estimates of Firm Performance Effects from Technological Uniqueness

Panel A: Baseline

	Technological Uniqueness	**Sales Growth**	**Tobin's Q**	**Profitabilit y**	**ROA**
	OLS	IV	IV	IV	IV
Models	(1)	(2)	(3)	(4)	(5)
Technology Uniqueness (HP30)		6.647***	8.237***	1.474***	1.102***
		(2.106)	(3.044)	(0.473)	(0.380)
R&D Tax Credit IV	-0.0911***				
	(0.0298)				
Additional Controls	See Table Notes				
Fixed Effects	Firm, Industry, Location				
Cragg-Donald F-stat	8.363				
Kleibergen-Paap p-value	0.00227				
Observations	16,400	16,400	16,400	16,400	16,400

Panel B: Chernozhukov et al. Post-Lasso IV

	Technological Uniqueness	**Sales Growth**	**Tobin's Q**	**Profitabilit y**	**ROA**
	OLS	IV	IV	IV	IV
Models	(1)	(2)	(3)	(4)	(5)
Technology Uniqueness (HP30)		6.323***	7.888***	1.397***	1.050***
		(1.774)	(2.593)	(0.398)	(0.323)
R&D Tax Credit IV	0.0947***				
	(0.0298)				
Additional Controls	See Table Notes				
Fixed Effects	Firm, Industry, Location				
Observations	16,400	16,400	16,400	16,400	16,400

Notes: Technological Uniqueness is measured as the normalized distance between a firm's patent portfolio and the average patent portfolio of its Hoberg–Phillips (HP) product-market industry, defined using each firm's 30 most product-similar peers (HP30). The R&D Tax Credit IV is based on annual state-level changes in R&D tax credits, providing exogenous variation in firms' R&D expenditures. Panel A presents the IV results with controls identical to those in Table 2 of the main text. Panel B presents the IV results with controls selected using a post-lasso method. All regressions include firm, location, and industry fixed effects. The sample is restricted to patenting firms only. Standard errors are clustered at the location-by-year level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A13: Identification of interaction term with one exogenous variable

We are interested in regressions of the type

$$Y = \beta_1 \cdot X + \beta_2 \cdot Z + \beta_3 \cdot (X \times Z) + \epsilon \tag{13.1}$$

where ϵ is an error term, X is a potentially endogenous variable (in our case a measure of technological uniqueness) and Z is an exogenous variable (in our case a measure of technological spillover shocks from peer firms). Importantly we allow for two features that are realistic in all of our empirical applications. First, the variable X is allowed to be endogenous, in other words $E[X \cdot \epsilon] \neq 0$. Second, we allow the endogenous variable X and the exogenous variable Z to be correlated, i.e. $Cov(X, Z) \neq 0$.

We are interested in the identification of the interaction effect β_3 since it captures how technological uniqueness mediates the effect of exogenous spillover shocks. They key assumption required is the following conditional independence assumption:

$$Z \perp \epsilon \,|\, X \tag{13.2}$$

In other words, given the observable measure of technological uniqueness X, the technological shock measure is independent of the error term in the interaction regression. To now prove that β_3 is identified, we introduce some notation to use the Frisch-Waugh Theorem on Partitioned

Regression. Let $XZ_{\perp\{1,X,Z\}}$ denote the residuals from a regression of the interaction term $X \times Z$ on a constant, and the variables X, Z; similarly, $Y_{\perp\{1,X,Z\}}$ are the residuals from a regression of Y on on a constant, and the variables X, Z. By the Frisch-Waugh Theorem, the OLS estimator is given by

$$\widehat{\beta_3} = \beta_3 + \frac{Cov(XZ_{\perp\{1,X,Z\}}, \epsilon)}{Var[XZ_{\perp\{1,X,Z\}}]} \tag{13.3}$$

Which will be unbiased if and only if

$$Cov(XZ_{\perp\{1,X,Z\}}, \epsilon) = 0 \tag{13.4}$$

Since $E[\epsilon] = 0$, this condition reduces to

$$E[XZ_{\perp\{1,X,Z\}} \cdot \epsilon] = 0 \tag{13.5}$$

Which using the Law of Iterated Expectations, can be rewritten as

$$E[E[XZ_{\perp\{1,X,Z\}} \cdot \epsilon \,|\, X]] = 0 \tag{13.6}$$

Which will only hold if the conditional expectation inside the unconditional expectation is zero:

$$E[XZ_{\perp\{1,X,Z\}} \cdot \epsilon \,|\, X] = 0 \tag{13.7}$$

It is here that we use the conditional independence assumption (2), since due to conditional independence, it is true that

$$E[XZ_{\perp\{1,X,Z\}} \cdot \epsilon \,|\, X] = E[XZ_{\perp\{1,X,Z\}} \,|\, X] \cdot E[\epsilon \,|\, X] \tag{13.8}$$

At the same time, by construction the residual $XZ_{\perp\{1,X,Z\}}$ is orthogonal to X, so that

$$E[XZ_{\perp\{1,X,Z\}}|X] = 0 \tag{13.9}$$

Using (13.9) in (13.8) then directly gives (13.6) and therefore (13.4) and (13.3). To summarize, under the condition of conditional independence of the shock and the error term conditional on the observable variable X, the interaction term β_3 is unbiased, even though the variable X is endogenous.

Appendix A14: IV Complier Analysis

A14.1 Method

According to a prominent view, strategic management should tailor business policy recommendations to suit specific types of companies or particular circumstances instead of offering "universal best practices" (Barney, 1986; Porter and Siggelkow, 2008). Barney (1986) pointed out that it is more beneficial to understand what makes certain companies successful in specific contexts, rather than looking for common strategies that every company in an industry could use. This is because targeted strategies are more likely to provide a competitive edge. Complier analysis is a method to empirically characterize the companies for which uniqueness causes better or worse performance. Therefore, complier analysis offers strategic recommendations that are more practical and directly applicable to certain firms but not others, making our guidance far more valuable for executives. At the same time, complier analysis allows us to empirically characterize how compliers differ empirically from the rest of the sample, leading to deeper understanding of why the quantitative magnitudes of IV estimates might differ from each other and from OLS results.

Complier firms are defined as firms that are responsive to an IV (Angrist and Pischke, 2009). The basic idea of this analysis is based on Angrist, Imbens and Rubin (1996) who showed that under some conditions, IV estimates reflect the causal effects of the treatment on the compliers instead of the whole sample of treated firms, which also includes "always takers", who would have taken treatment even without the encouragement of the instrument. We note that traditional complier analysis relies on binary instruments and binary treatment variables, in contrast to the continuous treatment variable of technological uniqueness and our continuous instrumental variables.[11] We therefore dichotomize the relevant variables in the following way. We construct a binary version of our instruments, denoted by E_i. E_i will be one for above average values for the Centroid IV, the R&D Tax Credit IV and the Patent Expiration IV. Our treatment variable T_i is derived from our measure of technological uniqueness. For the Centroid IV, our prediction is that stronger industry centroid changes will lead to more uniqueness at the focal firm, so we construct a treatment indicator T_i which is one if the technological uniqueness measure is above average and zero otherwise. In contrast for both the R&D Tax Credit IV as well as the Patent Expiration IV, our prediction is that higher values of the IV will induce less technological uniqueness. Therefore, for these variables, we construct a treatment indicator T_i which is one if the technological uniqueness measure is below average and zero otherwise. Following potential outcomes notation (Rubin, 1974), let $T_{1,i}$ denote the treatment value for firm i, when the instrument is $E_i = 1$ and $T_{0,i}$ for $E_i = 0$. Under this notation, and with the proper definition of treatment group T_i, compliers are defined as the set of firms for which $T_{1,i} - T_{0,i} > 0$, which is also called the "monotonicity assumption" in Angrist, Imbens and Rubin (1996). Under these definitions and assumptions, the fraction of compliers in the overall sample can be calculated as:

$$P\left(T_{1,i} > T_{0,i}\right) = P\left(T_i \,|\, E_i = 1\right) - P\left(T_i \,|\, E_i = 0\right) \quad \text{(A14.1)}$$

[11] We also note that standard complier analysis relies on a set of fully saturated controls. We have too many continuous control variables to generate saturated controls for all control variables and still have variation left over to analyze, and the literature does not currently offer a way to choose which control variables to saturate in a principled way.

Furthermore, the percentage of compliers relative to all treated firms can be calculated as

$$P\left(T_{1,i} > T_{0,i} \mid T_i = 1\right) = \frac{P\left(E_i = 1\right) \cdot \left(P\left(T_i \mid E_i = 1\right) - P\left(T_i \mid E_i = 0\right)\right)}{P(T_i = 1)} \tag{A14.2}$$

To show the empirical differences between compliers and average firms in the sample, we follow Angrist and Pischke (2009) and define indicator variables X_i, which are one if firm i exhibits an above-average value of some characteristic X and zero otherwise. Based on this and our other definitions, we will calculate the quantity

$$\frac{P\left(X_i = 1 \mid T_{1,i} > T_{0,i}\right)}{P\left(X_i = 1\right)} = \frac{P\left(T_i \mid E_i = 1, X_i = 1\right) - P\left(T_i \mid E_i = 0, X_i = 1\right)}{P\left(T_i \mid E_i = 1\right) - P\left(T_i \mid E_i = 0\right)} \tag{A14.3}$$

Equation (A14.3) shows how to calculate the odds of how much more likely complier firms are to exhibit above-average values for characteristic X than average firms in the sample. For example, values such as $\frac{P\left(X_i = 1 \mid T_{1,i} > T_{0,i}\right)}{P\left(X_i = 1\right)} = 1$ will mean that complier firms are about as likely to have above average characteristic X as the average firm in the sample. In contrast if $\frac{P\left(X_i = 1 \mid T_{1,i} > T_{0,i}\right)}{P\left(X_i = 1\right)} = 2$, then compliers are twice as likely as average firms with have an above-average value of X.

A14.2 Results

To shed further light on which companies the different IV estimates apply to, we follow the methodology outlined in the previous section and provide a complier analysis in Table A14.

Panel A of Table A14 shows that the percentage of compliers is small, ranging from 6.24% to 9% of the respective estimation samples. The instrument with the largest group of compliers is the Patent Expiration IV, for which compliers account of 9% of sample firms.

Appendix Table A9: Profiling Compliers Across Instruments

Panel A: Fraction of Compliers in Sample	Industry Centroid IV	Patent Expiration IV	R&D Tax Credit IV
	(1)	(2)	(3)
$P(E_i=1)$	54.74%	68.41%	54.56%
$P(T_i=1)$	40.97%	30.03%	21.47%
$P(T_{1i}\text{-}T_{0i})$	6.24%	9.00%	5.53%
Percentage compliers relative to all treated firms	8.33%	20.54%	14.06%

Panel B: Characterizing Compliers	Industry Centroid IV		Patent Expiration IV		R&D Tax Credit IV	
	(1)	(2)	(3)	(4)	(5)	(6)
	$P(T_{1i}\text{-}T_{0i}\|X_i=1)$	$P(X_i=1\|T_{1i}\text{-}T_{0i})$ $/P(X_i=1)$	$P(T_{1i}\text{-}T_{0i}\|X_i=1)$	$P(X_i=1\|T_{1i}\text{-}T_{0i})$ $/P(X_i=1)$	$P(T_{1i}\text{-}T_{0i}\|X_i=1)$	$P(X_i=1\|T_{1i}\text{-}T_{0i})$ $/P(X_i=1)$
High Growth	14.03%	2.24	9.65%	1.07	6.86%	1.23
High No. of Patents	7.68%	1.23	-10.6%	--	0.69%	0.12
High Market Concentration	5.17%	0.82	2.41%	0.26	1.01%	0.18
High Earnings Volatility	0.24%	0.038	13.13%	1.45	13.74%	2.48
High R&D	16.73%	2.68	0.56%	0.06	8.89%	1.60
High Intangible Capital	4.74%	0.76	17.02%	1.89	3.26%	0.59

Notes: Characteristics dummy $X_i = 1$ if the characteristic value is above the average value in the sample. Characteristics include: "Growth": sales growth in past 3 years, "No. of Patents": number of patents; "Market Concentration": Herfindahl index in industries the firms is active in; "Earnings Volatility": Coefficient of variation for firm earnings in the past 3 years; "R&D": R&D as ratio to sales; "Intangible capital": intangible capital items as fraction of assets. Complier results are estimated using a logistic regression. For the Industry-Centroid IV and R&D tax credit IV, fixed effects include firm, industry and region fixed effects. For the Patent Expiration IV, fixed effects include firm, industry, region, and year. For column (1) T_i is dummy variable that is one if a firm has above-average technological uniqueness (the "treatment group"). For columns (2), (3) T_i is dummy variable that is one if a firm has below-average technological uniqueness. E_i is a dummy that is one if the instrumental variable (Centroid IV, R&D tax credit IV, Patent Expiration IV) has an above-average value. Correspondingly, $P(T_i=1)$ is the fraction of treated firms; $P(Z_i=1)$ is the fraction of firms with above average instrument values; $P(T_{1i}\text{-}T_{0i})$ is fraction of "complier" firms, which are defined as responding to the instrument by increasing technological uniqueness; X_i is a dummy that is one for firms that have above-average values of characteristics X given in the rows of Panel B; $P(T_{1i}\text{-}T_{0i}|X_i=1)$ is the fraction of compliers, conditional on firms with above-average characteristic X; $P(X_i=1|T_{1i}\text{-}T_{0i})$ $/P(X_i=1)$ measures how much more likely compliers are to exhibit above-average characteristic X compared to average sample firms. Whenever estimates of $P(X_i=1|T_{1i}\text{-}T_{0i})$ are negative, we replace $P(X_i=1|T_{1i}\text{-}T_{0i})$ $/P(X_i=1)$ with a lower bound of zero. For more details, see text and Angrist and Pischke (2009).

Panel B of Table A14 documents that the complier groups across all three IVs are very different. The key entries are the even number columns, i.e. column (2), (4) and (6) as these columns show how much more likely firms in the complier group are to have firms with above-average characteristic X, compared to average firms in the sample. For example, in the first row, the characteristic X is having "High Growth" and the first entry of column (2) says that compliers of the Industry Centroid IV are 2.24 times more likely to have above-average sales growth in the prior 3 years. In other words, firms with high sales growth rates benefit from the use of non-rival or scale-free resources such as technological uniqueness, exactly as we discussed in section 2.1.

Industry Centroid-IV compliers also 2.68 times more likely to have above-average R&D spending, 23% more likely to generate an above-average number of patents, and are 96% less likely to exhibit above-average earnings volatility. Large and positive causal performance effects of higher technological uniqueness therefore especially apply to firms that can benefit from the scale-free nature of technological uniqueness while strongly and successfully investing R&D and successfully patenting, while keeping idiosyncratic profit volatility low.

Patent Expiration-IV compliers are very different in nature. They are firms that suffer large performance drops from lower technological uniqueness, as shown in Panel B of Table 3 in the main paper. Column (4) of Panel B in Table A9 shows that these firms are 94% less likely to have above-average R&D spending, but instead are 89% more likely to have above-average other intangible capital and are 45% more likely to exhibit above-average earnings volatility. From these systematic empirical patterns emerges a picture of firms that are not technologically innovative, but instead try to use intangible assets such as brand names to compete. Such firms are hurt disproportionately by their efforts to use outdated technology, which tends to make them more similar to their competitors, thereby exposing them to more competitive pressure.

Finally, column (6) of Panel B in Table A9 characterizes R&D tax credit compliers. Unsurprisingly, these firms are 60% more likely to have above-average R&D spending. This is expected, as high amounts of R&D investment also means that benefits from R&D tax credits are higher. At the same time, R&D tax credit compliers are 88% *less* likely to have above-average number of patents. This again is consistent with the logic of our R&D tax credit identification strategy: if a firms does not invest in R&D but-for receiving a tax credit, its innovative activity is likely to be marginal instead of very novel and unique. At the same time, the results show that R&D tax credit compliers are 2.48 times more likely to have above-average earnings volatility, which is qualitatively similar to Patent Expiration IV compliers.

As this complier analysis shows, the three groups of firms are empirically very distinct from each other. Yet, for all three groups of compliers, our IV analysis robustly finds causal impacts of technological uniqueness on firm performance: positive performance effects from more technological uniqueness and negative performance effects from less technological uniqueness. These findings are indicative of the robustness of the causal estimates, while highlighting the importance of the characteristics of firms that either tend to disproportionately benefit from more technological uniqueness or tend to be strongly hurt by reductions in technological uniqueness.

Appendix A15: Interaction regressions with IV for TU

We examine whether the performance effects of TU vary with firms' innovation effort and local product-market concentration.

Table A15: Interaction Regressions with IV

Panel A: R&D Intensity TU

	Sales Growth	Tobin's Q	Profitability	ROA
Models	(1)	(2)	(3)	(4)
Technology Uniqueness	0.715**	2.311	0.132	0.0177
	(0.328)	(1.643)	(0.0897)	(0.126)
TU x R&D Intensity	-3.965	-20.55	-0.0112	0.728
	(3.470)	(19.63)	(0.732)	(1.155)
R&D Intensity	-2.595	-13.21	-0.136	0.165
	(2.234)	(12.64)	(0.477)	(0.753)
Fixed effects	Firm, Location, Industry, Year			
Standard Errors	Clustered at the firm level			
R-squared	-	-	-	0.153
Observations	17604	17604	17604	17604

Panel B: HHI TU

	Sales Growth	Tobin's Q	Profitability	ROA
Models	(1)	(2)	(3)	(4)
Technology Uniqueness (HP30)	0.886*	2.878	0.167	0.00471

	(0.527)	(1.850)	(0.152)	(0.144)
TUxHHI	-0.515	-1.755	-0.0993	0.0420
	(0.838)	(2.820)	(0.218)	(0.182)
Average HHI	0.0389	0.0387	-0.0142	-0.0319
	(0.233)	(0.773)	(0.0540)	(0.0409)
Fixed effects	Firm, Location, Industry, Year			
Standard Errors	Clustered at the firm level			
R-squared	-	-	-	-
Observations	17604	17604	17604	17604

Notes: Technological Uniqueness is measured as the normalized distance between a firm's patent port average patent portfolio of its Hoberg–Phillips (HP) product-market industry, defined using each firm product-similar peers (HP30). R&D Intensity is defined as R&D expenditures divided by sales. Avera as average Herfindahl–Hirschman Index (HHI) by industry. All regressions include firm, location, ind fixed effects. The sample is restricted to patenting firms, and controls are identical to those in Table 2 Standard errors are clustered at firm-level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Appendix A16: Controlling for Industry Uniqueness

Much of our conceptual discussion of the performance effects of technological uniqueness has argued technological uniqueness introduces a new set of considerations on technology spillovers that make it quite distinct from the general strategic positioning and resource logic of Litov et al. (2012). However, a natural empirical question is whether technological uniqueness really just captures the effects of industry uniqueness instead of the distinct effects of technological resources. To investigate this potential issue, we follow Litov et al. (2012) and measure industry uniqueness, defined as the degree to which a firm's vector of sales across business segments differs from the centroid vector of sales across business segments of all firms within its industry.

Table A16 shows that controlling for product market uniqueness, both independently and in interaction with technological uniqueness, has little effect on our main coefficient estimates from Table 2, confirming that the performance effects we attribute to technological uniqueness are not merely capturing differences in product market positioning.

Table A16 Performance Metric Regressions: Product Market Uniqueness

Panel A:	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
Models	(1)	(2)	(3)	(4)
Technology Uniqueness (HP30)	0.0221***	0.0830***	0.00419*	0.00494*
	(0.00652)	(0.0255)	(0.00244)	(0.00276)
	-0.00170	0.00473	0.000664	-0.000156
Product Market Uniqueness	(0.00360)	(0.0137)	(0.00139)	(0.00159)
Additional Controls	See table notes.			
Fixed effects	Firm, Industry, Region, Year			
Standard Errors	Clustered at the firm level			
R-squared	0.0831	0.0590	0.221	0.151
Observations	18257	18257	18257	18257

Panel B:	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
Models	(1)	(2)	(3)	(4)
Product Market Uniqueness	-0.00133	0.00613	0.000735	-0.0000734
	(0.00361)	(0.0137)	(0.00139)	(0.00159)

Additional Controls	See table notes.			
Fixed effects	Firm, Industry, Region, Year			
Standard Errors	Clustered at the firm level			
R-squared	0.0820	0.0575	0.221	0.150
Observations	18257	18257	18257	18257

Panel C:	**Sales Growth**	**Tobin's Q**	**Profitability**	**ROA**
Models	(1)	(2)	(3)	(4)
Technology Uniqueness (HP30)	0.0219***	0.0825***	0.00421*	0.00493*
	(0.00655)	(0.0256)	(0.00245)	(0.00277)
Product Market Uniqueness	-0.00190	0.00398	0.000681	-0.000173
	(0.00361)	(0.0140)	(0.00139)	(0.00159)
Technology Uniqueness x Product Market Uniqueness	0.00275	0.0102	-0.000228	0.000225
	(0.00336)	(0.0133)	(0.00121)	(0.00143)
Additional Controls	See table notes.			
Fixed effects	Firm, Industry, Region, Year			
Standard Errors	Clustered at the firm level			
R-squared	0.0831	0.0590	0.221	0.151
Observations	18257	18257	18257	18257

Notes: Product market uniqueness is measured as the normalized distance from the average industry business segment portfolio. Technological Uniqueness is measured as the normalized distance betwee a firm's patent portfolio and the average patent portfolio of its Hoberg–Phillips (HP) product-market industry, defined using each firm's 30 most product-similar peers (HP30). Panel A includes both uniqueness measures as explanatory variables. Panel B includes only product market uniqueness, whi Panel C adds the interaction term between the two. All regressions include firm, location, industry, ar year fixed effects. The sample is restricted to patenting firms, and controls are identical to those in Ta 2 of the main text. Standard errors are clustered at firm-level. Statistical significance levels: *: 10%, * 5%, ***: 1%.

Appendix A17: Controlling for Self-Citations

As we discuss in section 2.2 of the main paper, our analysis of technological uniqueness is quite different from considerations of firm-specific knowledge resources as in Wang et al. (2009). However, one might wonder whether our measure of technological uniqueness really reflects self-citation scores as a measure of firm-specific knowledge resources.

Table A17: Controlling for Self-Citations

	Sales Growth	**Tobin's Q**	**Profitability**	**ROA**
	(1)	(2)	(3)	(4)
Technology Uniqueness (HP30)	0.0249***	0.0695**	0.00671***	0.00635**
	(0.00679)	(0.0274)	(0.00228)	(0.00267)
Share of Self-Citations	-0.0247	-0.118**	-0.00165	-0.00532
	(0.0157)	(0.0585)	(0.00588)	(0.00690)
Additional Controls	See table notes.			
Fixed effects	Firm, Location, Industry, Year			
R-squared	0.0900	0.0644	0.216	0.143
Observations	15,942	15,942	15,942	15,942

Notes: Share of self-citations is the share of the focal firm's new patents that cite their own patents over the total number of patent citations by the firm that year. Technological Uniqueness is measured as the normalized distance between a firm's patent portfolio and the average patent portfolio of its Hoberg–Phillips (HP) product-market industry, defined using each firm's 30 most product-similar peers (HP30). All regressions include firm, location, industry, and year fixed effects. The sample is restricted to patenting firms, and controls are identical to those in Table 2 of the main text. Standard errors are clustered at firm-level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

Table A17 shows that this is not the case. If anything, the correlations of firm performance and technological uniqueness end to be somewhat stronger when controlling for industry uniqueness.

Appendix A18: Exit and Survivorship Bias

Another potential issue is that our performance results might be driven by survivorship bias. Specifically, there are two distinct ways in which the set of continuing public firms might be sample selected. On the one hand, technologically unique firms might generally be more risky, which leads badly performing technologically unique firms to go into bankruptcy (see Yang, Li, and Kueng, 2021). If this would be the case, the fact that technologically unique firms outperform non-unique firms might just reflect the higher risk that technologically unique firms exhibit. On the other hand, even if worse performing technologically unique firms do not exit the sample through bankruptcy, they might exit through LBOs or acquisitions, again leaving the outperforming technologically unique firms as a reflection of sample selection in our data.

We analyze both of these possible concerns by taking advantage of Compustat's exit variables, that encode whether firms exit the data because of bankruptcy, LBOs or acquisitions.[12] If technologically unique firms are really riskier, we would expect that technological uniqueness is positively correlated with these three forms of exit.

Table A18: Exit and Survivorship bias

	Bankruptcy	**LBO**	**Acquisition**
	(1)	(2)	(3)
Technology Uniqueness (HP30)	0.000641	0.000470*	0.0000141
	(0.000553)	(0.000270)	(0.00279)
Additional Controls	See table notes.		
Fixed effects	Firm, Location, Industry, Year		
R-squared	0.00257	0.000765	0.00423
Observations	19,536	19,536	19,536

[12] The number of exit events we observe in our sample of patenting Computat firms are 23 for bankruptcy, 19 for LBO and 710 for acquisitions.

Notes: Technological uniqueness is measured as the normalized distance from average industry patent portfolio. Industries are defined using the Hoberg–Phillips product-market similarity scores, based on each firm's 30 most similar peers. Exit variables capture firm outcomes through bankruptcy, leveraged buyout (LBO), or acquisition events. All regressions include firm, location, industry, and year fixed effects. The sample is restricted to patenting firms, and controls are identical to those in Table 2 of the main text. Standard errors are clustered at firm-level. Statistical significance levels: *: 10%, **: 5%, ***: 1%.

As Table A18 shows, there is at best only very noisy statistical evidence for technological uniqueness being related to LBOs, but no systematic evidence for a relation between technological uniqueness and exit.